Science of the Total Environment xxx (2017) xxx–xxx

Contents lists available at ScienceDirect

Science of the Total Environment

journal homepage: www.elsevier.com/locate/scitotenv

Spatial distribution of soil chemical properties in an organic farm in Croatia

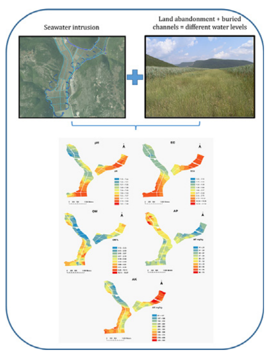
Igor Bogunovic [a,*], Paulo Pereira [b], Eric C. Brevik [c]

[a] University of Zagreb, Faculty of Agriculture, Department of General Agronomy, Zagreb, Croatia
[b] Environmental Management Center, Mykolas Romeris University, Ateities g. 20, LT-08303 Vilnius, Lithuania
[c] Department of Natural Sciences, Dickinson State University, Dickinson, ND, USA

HIGHLIGHTS

- Spatial variability of pH, OM, EC and plant available P and K was investigated.
- Ordinary kriging and co-kriging techniques were tested.
- The soils studied had high pH, EC, OM and AK levels, while AP content was low.
- The spatial variability was high for EC and low for pH levels.
- Interpolations with auxiliary information improved mapping.

GRAPHICAL ABSTRACT



ARTICLE INFO

Article history:
Received 12 December 2016
Received in revised form 9 January 2017
Accepted 10 January 2017
Available online xxxx

Keywords:
Auxiliary data
Co-kriging
Nutrient maps
Geostatistics

ABSTRACT

Soil pH, electrical conductivity (EC), organic matter (OM), available phosphorus (AP), and potassium (AK) are some of the most important indicators of soil fertility. These soil parameters are highly variable in space and time, especially in agricultural areas, with implications for crop production. The aim of this work was to study the spatial variability of pH, EC, OM, AP and AK using kriging and co-kriging methods in the Rasa River Valley (Croatia). As co-variates for each variable we considered the distance from the sea (DFS), distance from the river channels (DFC), pH, EC, OM, AP and AK. Only the variables with a significant correlation with the predictor were used as predictor variables. The results showed that soils of the study area had high pH, EC, OM and AK values and a low concentration of AP. The spatial variability was high for EC and low for pH levels. pH, EC, OM and AK had significant positive correlations. All these variables had significant negative correlations with AP. The exponential model was the best to model OM, AK and AP. Spherical and Gaussian models were the most accurate to model pH and EC. Spatial dependence was high for soil AK, EC and pH, and moderate for soil OM and AP. The incorporation of auxiliary variables increased the precision of the estimations. CoK_DFS was the best method to predict soil EC and AP, while Cok_EC, was better to estimate soil pH and Cok_pH and Cok_OM predicted soil OM and AK with the best accuracy. The maps produced with the best predictors showed that pH, EC, OM and AK had high levels in the northern and eastern parts of the study area. The opposite trend was identified in relation to the AP spatial pattern.

* Corresponding author.
E-mail addresses: ibogunovic@agr.hr (I. Bogunovic), pereiraub@gmail.com (P. Pereira), eric.brevik@dickinsonstate.edu (E.C. Brevik).

http://dx.doi.org/10.1016/j.scitotenv.2017.01.062
0048-9697/© 2017 Elsevier B.V. All rights reserved.

1. Introduction

The current use of unsustainable agricultural practices is contributing to decreased soil fertility (Keesstra et al., 2016a; Khaledian et al., 2016a). These practices reduce soil organic carbon (Dawson and Smith, 2007; McCarl et al., 2007; Lal, 2009; Padmanabhan et al., 2013; Carr et al., 2015), soil structure (Cerdà, 2000; Carbonell-Bojollo et al., 2011; Bremenfeld et al., 2013), and increase soil compaction (Soane, 1990; Défossez et al., 2014) and erosion (García-Díaz et al., 2016; Keesstra et al., 2016b; Rodrigo Comino et al., 2016). Excessive nitrogen fertilization often leads to soil acidification (Haynes and Swift, 1986; Juo et al., 1995; Horswill et al., 2008; Guo et al., 2010), reducing the availability of important elements for plant nutrition such as calcium, phosphorous and potassium (Blake et al., 1994; Horswill et al., 2008; Guo et al., 2010; Tang et al., 2011) and producing negative impacts on human health (Brevik and Sauer, 2015). Intense soil irrigation increases the concentration of salts (Qadir and Oster, 2004; Ouni et al., 2013; Wichelns and Qadir, 2015; Zewdu et al., 2015), especially in semiarid, arid, and coastal regions (Akhter et al., 2004; Singh et al., 2013; Ranjbar and Jalali, 2016). All these practices contribute to land degradation.

Soil chemical elements have a high spatial variability, especially in agricultural areas. For the application of sustainable soil management practices, it is essential to know the spatial distribution of soil properties to be able to identify areas that require intervention and the level at which those interventions are needed. The spatial variability of soil nutrients is affected by parent material characteristics, topography, climate, vegetation, time and anthropogenic activities (Fenton and Lauterbach, 1998; Johnson et al., 2000; Umali et al., 2012; Keesstra et al., 2016a, 2016b; Mulder et al., 2016). Several studies have investigated the spatial variability of soil pH (Robinson and Metternicht, 2006; Fu et al., 2010; Bogunovic et al., 2014; Behera and Shukla, 2015), organic matter (Bogunovic et al., 2014; Behera and Shukla, 2015; Yang et al., 2016a), electrical conductivity (EC) (Robinson and Metternicht, 2006; Heilig et al., 2011; Behera and Shukla, 2015; Ranjbar and Jalali, 2016), phosphorus (Fu et al., 2010; Romic et al., 2012; Bogunovic et al., 2014; Behera et al., 2016; Wilson et al., 2016) and potassium (Fu et al., 2010; Bogunovic et al., 2014; Behera and Shukla, 2015). A good understanding of soil properties distribution will contribute to better soil management in agricultural areas (Brevik et al., 2003). This is very important for farmers to make sustainable use of their lands.

Geostatistical methods are widely employed to assess the spatial distribution of soil properties in agricultural areas (Robinson and Metternicht, 2006; Fu et al., 2013; De Paz et al., 2015) and contribute to better land use management (Nael et al., 2004; Liu et al., 2016). There are many different univariate kriging methods used with soil variables (e.g. ordinary kriging, disjunctive kriging, indicator kriging). The models and maps produced by these techniques show the spatial variation of the variable of interest, but ignore interrelations with other environmental variables (co-variates) at the site (Lv et al., 2013). The use of auxiliary variables is advantageous to estimate the variable of interest during the analysis because it allows the analyst to determine if the spatial distribution of a determined variable is dependent upon other(s). These analyses are carried out using hybrid methods, such as co-kriging (Wen et al., 2015). The use of auxiliary variables normally increases the accuracy of the spatial predictions as observed in previous works (Stein and Corsten, 1991; Zhang et al., 1992; Yang et al., 2016b; Ceddia et al., 2015; Chen et al., 2016). Nevertheless, several works observed that the use of co-variates did not improve the accuracy of the interpolation (Martínez-Cob, 1996; Castrignano et al., 2011; Ceddia et al., 2015). This lack of improvement was attributed to the lack of or low correlation between the predictor(s) and the predicted variable. It follows that the performance of successful co-kriging depends on the use of proper auxiliary variables. The production of accurate maps is necessary for sustainable land management of agricultural areas. They will be the basis for restoration of degraded areas, and thus for a proper investment of the resources available, therefore it is essential that they be as accurate as possible (Brevik et al., 2016; Pereira et al., in press). In this context, it is important to investigate different co-variates and compare them in order to identify the least biased predictors that can be used to produce the best map to assist in land management. The aim of this work was to study the spatial distribution of soil pH, soil organic matter (OM), plant available phosphorus (AP), potassium (AK), and electrical conductivity (EC) in the soils of a Croatian organic farm using geostatistical methods. The specific objectives of this paper are: (i) to assess the correlations among soil properties, (ii) to examine the spatial structure and variability of soil properties through semi-variogram modelling, (iii) test several univariate and multivariate geostatistical techniques to find the best predictor for the studied soil properties (iv) and map the spatial distribution of soil properties using the most accurate model.

2. Materials and methods

2.1. Study area

The study area is located on the Istria peninsula (45°3′ N; 14°2′ I; average elevation −2 m below sea level), with a total area of 182 ha, divided into several parts by river channels (Fig. 1). The elevation decreases from north to south. A large part of the study area is below sea level and this necessitates pumping and draining excess water. A dam covers the south area and prevents the penetration of sea water into the valley. This land had been abandoned for at least two decades and covered with natural grasses and cane before cultivation began in 2015. The climate of the study area is Mediterranean. Mean annual temperature ranged from 12.2 °C to 15.2 °C and the average annual precipitation varied from 476 mm to 1444 mm between 1978 and 2014. Soils over the majority of the study area are classified as silty clay loam Anthrosols, while silty loam Colluvium soils and Gleysoils are found in some areas (Table 1).

2.2. Sampling design and laboratory analyses

One hundred eighty-two soil samples (0–30 cm) were collected during July of 2015. The study area was divided into a regular grid with each box within the grid being approximately 100 × 100 m (Fig. 1). A Trimble Geo 7× GPS with 10 cm accuracy was used to record the georeferenced coordinates. Each soil sample corresponds to a composite of subsamples taken from 15 to 20 points from a diameter of 30 m. Composite sampling is often used to overcome small scale variability of soil properties in order to mitigate outliers and extremes that may occur if investigators used individual samples for mapping an area of interest. Individual samples were mixed in a bucket and taken to the laboratory for analysis. This methodology was used in previous works (Sollitto et al., 2010; Winowiecki et al., 2016). Soil samples were air dried in the laboratory for seven days at room temperature and sieved with a 2 mm mesh. Soil pH was determined using the electrometric method in a 1:2.5 (*w*/*v*) soil:solution ratio with a Beckman pH-meter Φ72 in a KCl solution. Electrical conductivity (EC) was calculated at 25 °C on soil:water (1:5) extract according to HRN ISO 11265, 2004. Soil OM was determined by a wet combustion procedure (Walkley and Black, 1934). Available P and K were extracted by ammonium lactate solution (Egnér et al., 1960) and detected by spectrophotometry and flame photometry.

2.3. Statistical analysis

Some descriptive analyses were carried out, such as minimum, maximum, arithmetic mean, standard deviation (SD), coefficient of variation (CV), kurtosis (Kur) and skewness (Skew). Shape parameters indicated non-normality of data distributions, while the presence of high skewness indicates serious departure from normality (Webster, 2001). In